



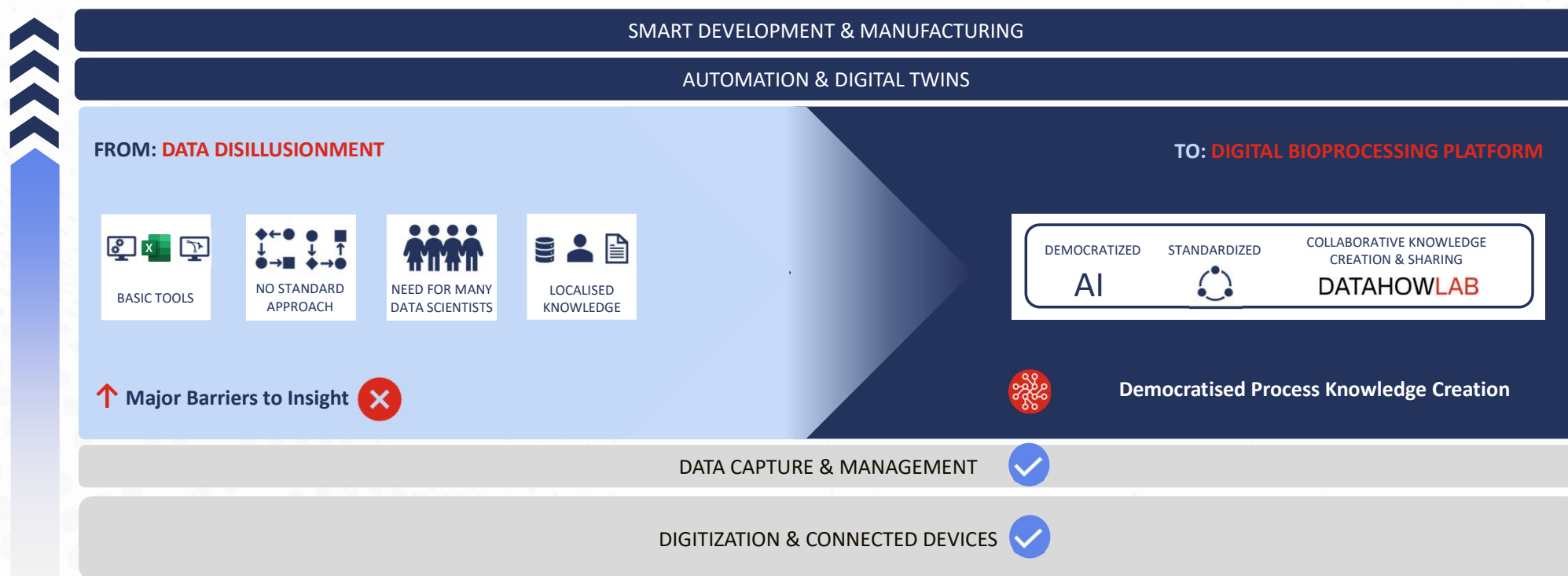
Transforming Process Development with AI-Technologies and a Digital Development Framework

AI-enabled Digital Bioprocessing

Alessandro Butté | CEO DataHow

AI & Advanced Analytics the next Milestone towards Pharma 4.0

Current approaches creating bottlenecks



AI-Technologies democratizing Access to deep process knowledge and the creation of Digital Twins



Transfer Learning

AI-enabled transfer of historical process knowledge across projects and scales to **reduce experimental effort and accelerate development**



Hybrid Models (AI)

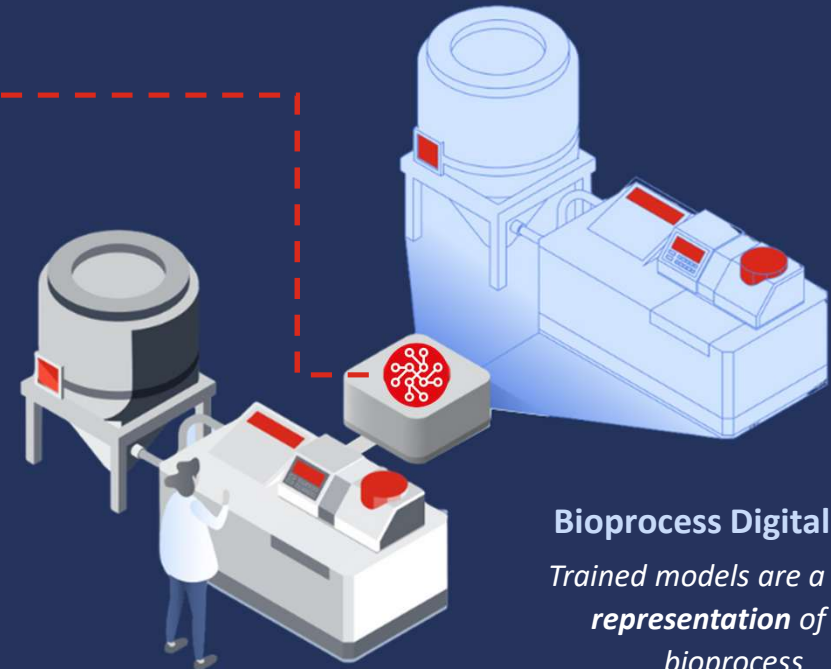
AI-enhanced models adapted to bioprocessing for **accelerated learning & insight with less data**



Risk-Based Decision Support

(Bayesian Statistics)

Outcomes & analysis assessments based on **probabilities**

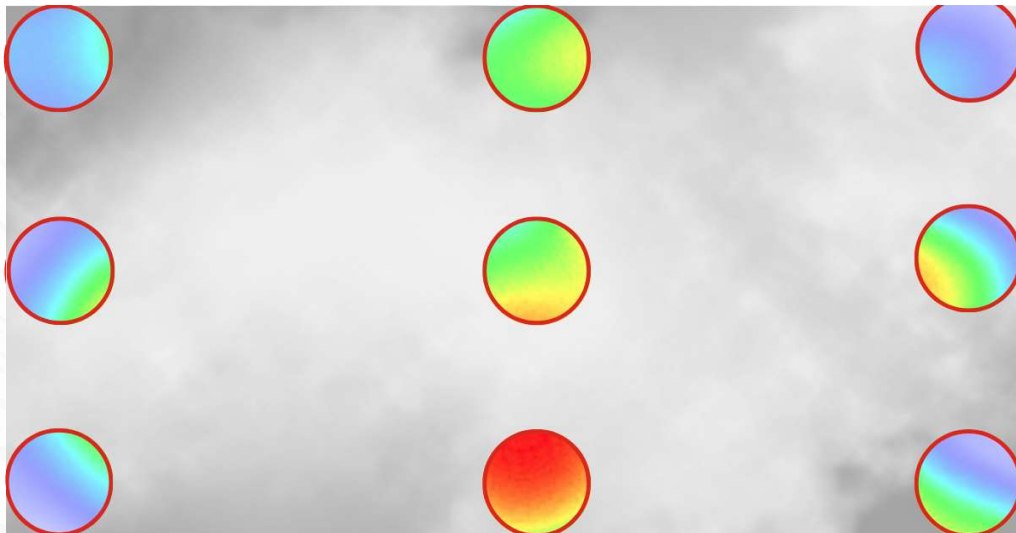


Bioprocess Digital Twin

Trained models are a **digital representation** of the bioprocess

A Paradigm Shift for Experimental Planning & Design

Traditional Approach: DoE & Statistical Models

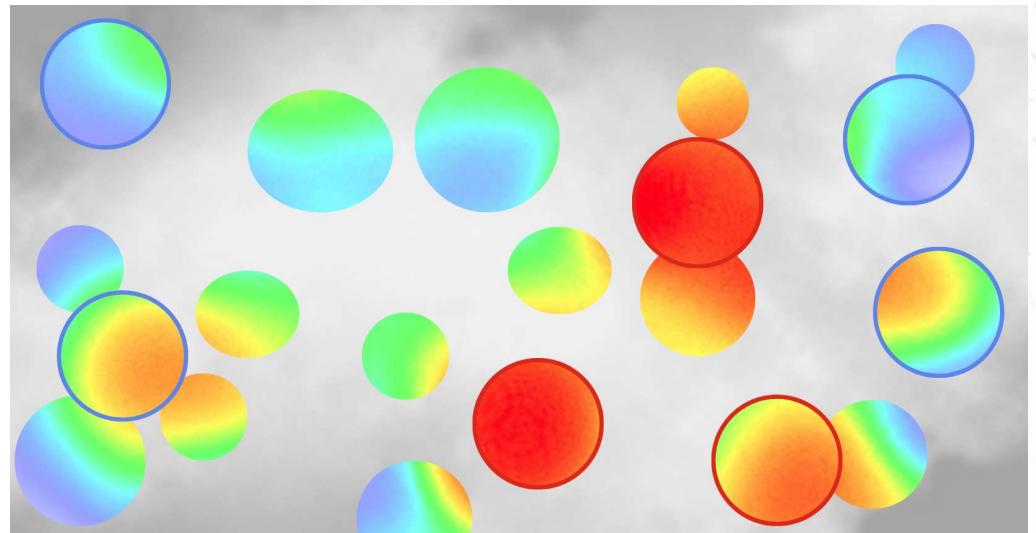


Fully dependent on new experimental data & analysis

Not leveraging existing bioprocessing knowledge

No learning from prior project data or insights

AI-driven Experimental Planning & Optimal Design



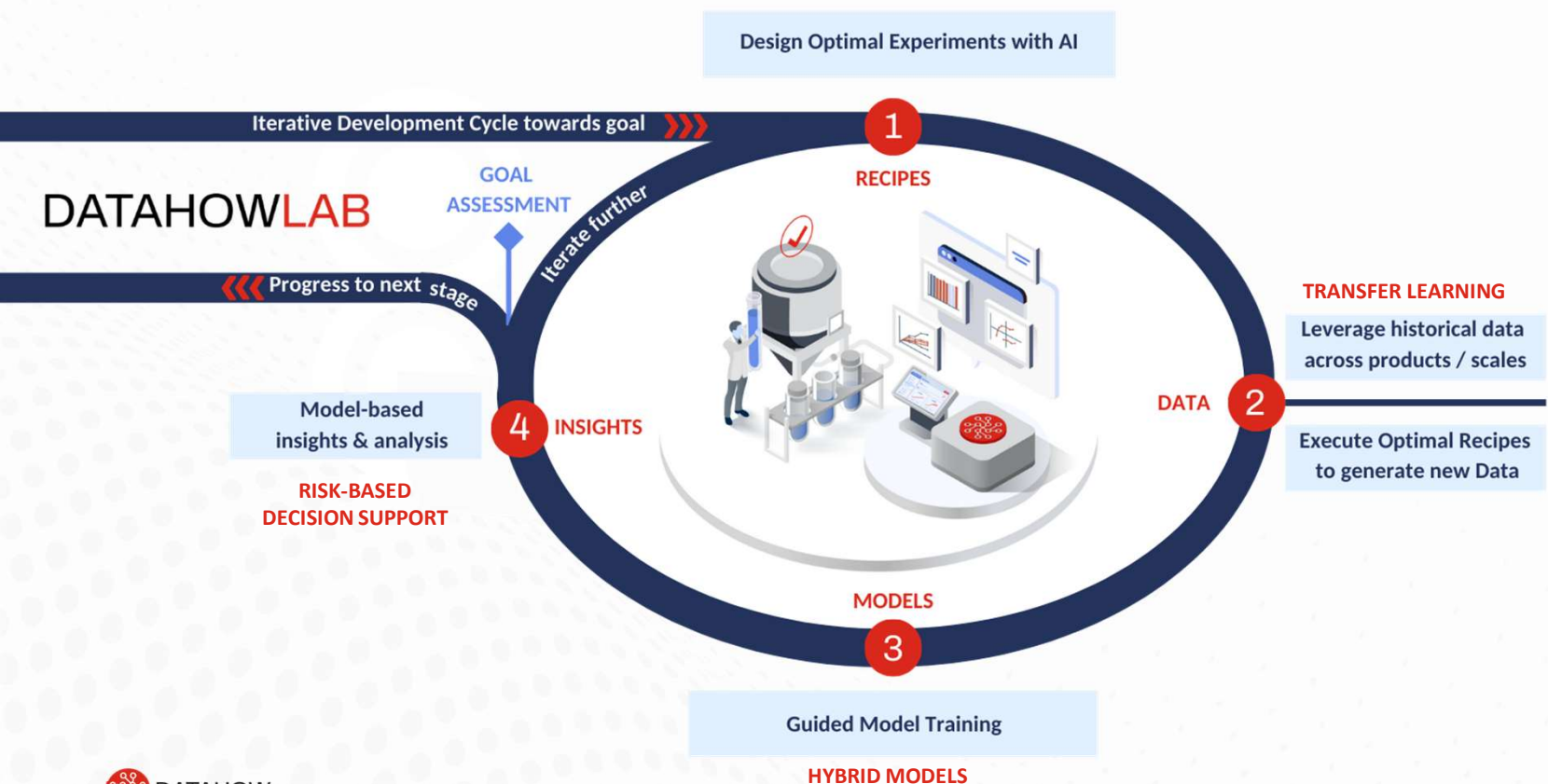
Fewer Targeted Experiments: **EXPLORE** gaps or **EXPLOIT** potential

 **Hybrid Models:** Bioprocessing knowledge encoded mechanistically

 **Transfer Learning:** transfer relevant historical project data & insights

Harnessed within a Digital Development Cycle

AI-Enabled Digital Bioprocessing Platform



THAT SUPPORTS
PROCESS STAKEHOLDERS



TO BUILD THE CORE ELEMENTS OF
PROCESS KNOWLEDGE

RECIPES

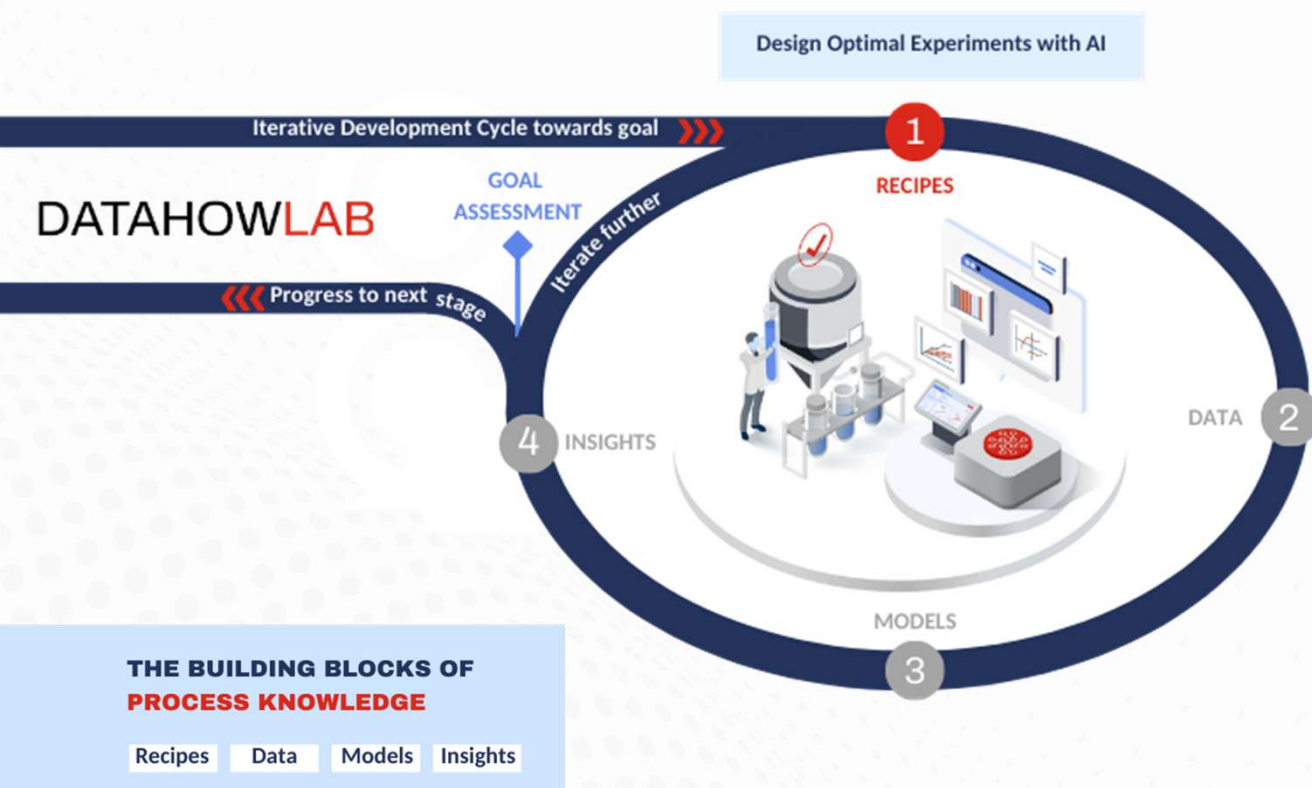
DATA

MODELS

INSIGHTS

Design & Execute Shorter, High-Value, Experiment Cycles







































Faster time, and lower cost to insight – iterate with supporting insight



1 RECIPES

- Experimental Designs which are optimized for the capabilities of Hybrid Models to **maximise insight with minimal, targeted, experimental data**
- Short, agile experimental cycles vs. extensive DoE waves to **reduce time and cost to insight and progress**

DoE WAVE 1

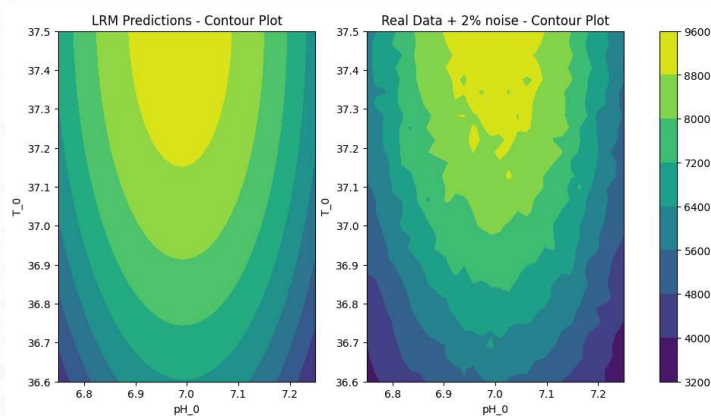
CYCLE 1	      	     
CYCLE 2	      	     
CYCLE 3	     	     

LHS + Hybrid Model vs Classical DOE

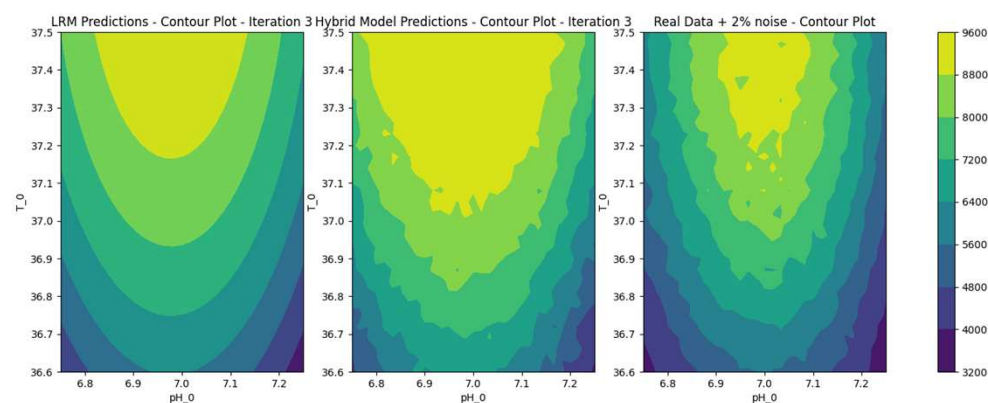
Much more with much less

Target R^2 : 90%

3 level FD – Reduced space – ca. 50 runs



Hybrid Model – Full Space – 20 runs



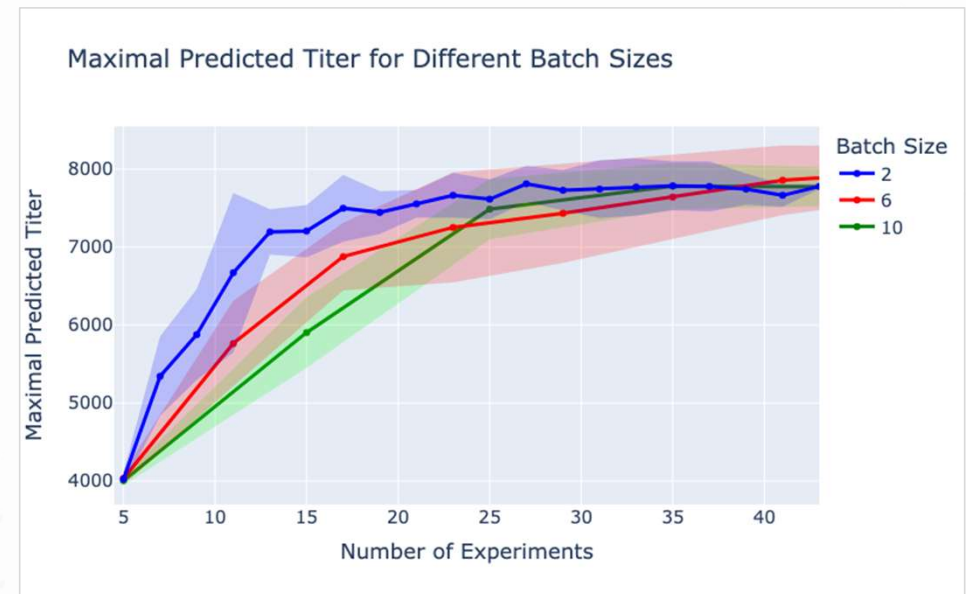
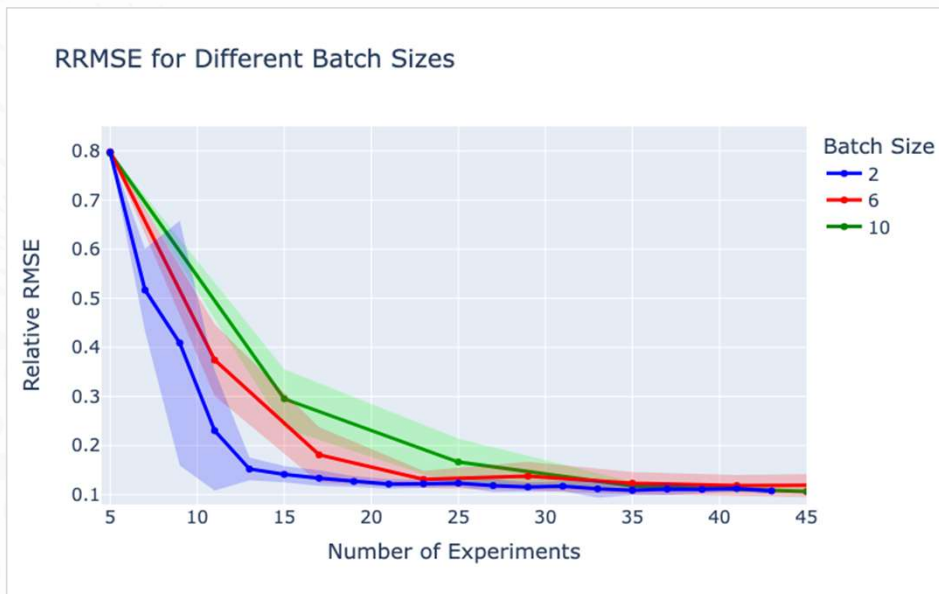
Variable	pH ₀	pH _{after_switch}	T ₀	T _{after_switch}	Glc _{feed}	Gln _{feed}
Upper Bound	6.75	6.76	36.6	35.09	4.76	9.46
Lower Bound	7.25	7.46	37.5	35.59	5.66	9.96

Variable	pH ₀	pH _{after_switch}	T ₀	T _{after_switch}	Glc _{feed}	Gln _{feed}
Upper Bound	6	6	36	35	2	6
Lower Bound	8	8	38	38	6	10

Validation Case: Hybrid Model for Cell Cultures

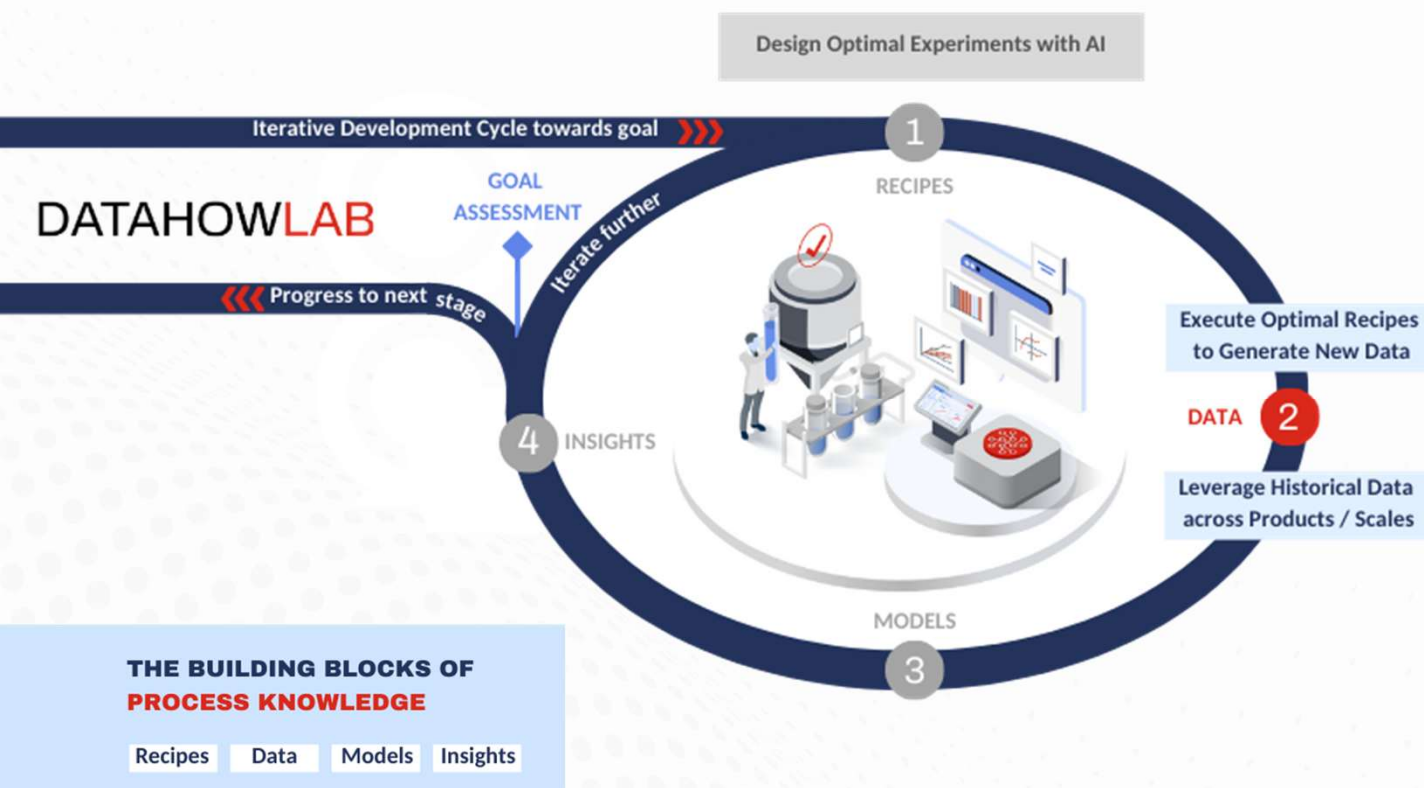
The Bayesian optimization methodology confirms the findings of the first study case

- Insilico Hybrid Model with 8 factors



Leverage Historical Data as a Development Asset

Reduce Experimental Effort and Drive Development Efficiency



2 DATA

- Generate new Experimental Data



- Compliment Experimental Data with Data from Relevant Historical Projects → **Transfer Learning**



TRANSFER LEARNING CASE STUDY REVIEW



Selected Case: Accelerate Clone Selection via Transfer Learning

Predicting molecule specific behaviour (Molecule - D) with only 3 runs

Historical
Molecules



A – 15 runs

B – 15 runs

C – 15 runs

D - 3 runs

Predicted values

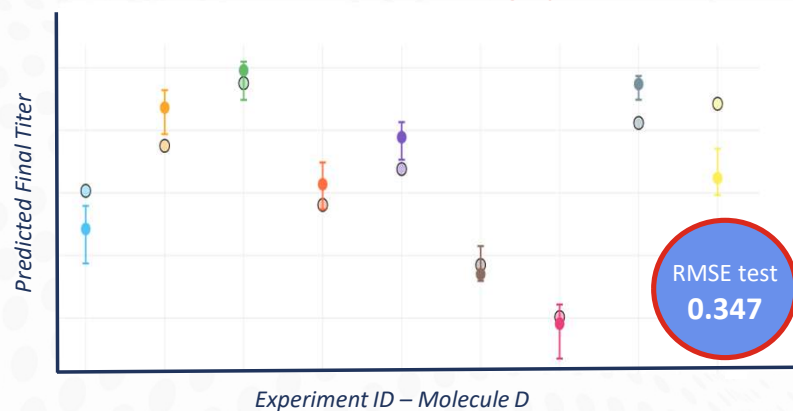


Model trained on 15 runs of molecules A, B & C + 3 runs of D

- The behaviour of molecule D can be learned effectively from only 3 runs of D and transferred knowledge from molecules A-C.
- Transfer learning can significantly accelerate clone selection process
- The trained model could suggest optimal clone choice & process design

→ **IMPACT: Reduction of Runs / Accelerated Development**

→ Predicted vs Test illustrates **high prediction accuracy**

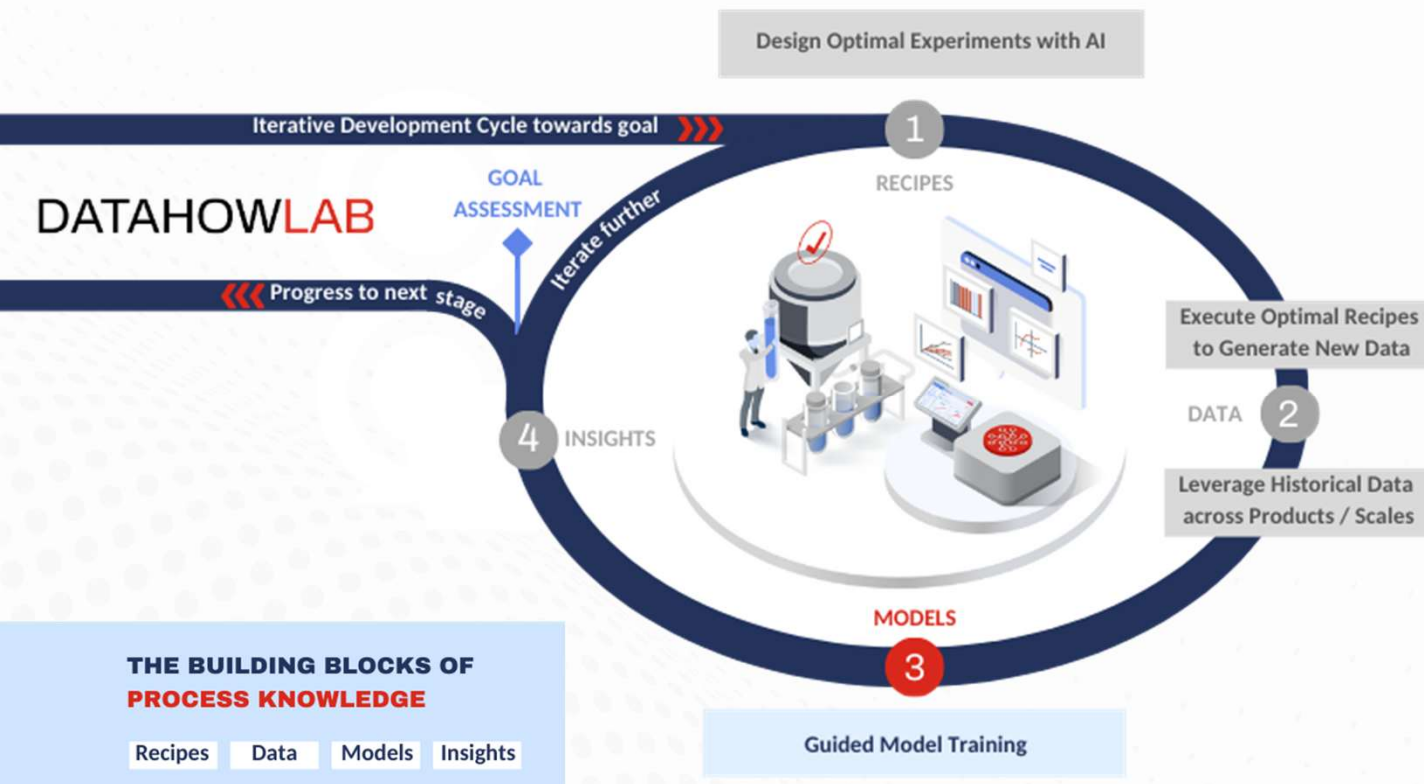


Transfer learning can also be applied **across scales**

We have been able to learn and **predict large-scale titers** with no or only 1 mid-scale run before continuing to pilot scale.



Realise more Insight with Less Experimental Effort



3 HYBRID MODELS

- No-code, guided workflows, making model training and accessible to process scientists



- Use DataHow's transformative Hybrid Modeling technology to **maximize insight** and learning with **minimal experimental effort**

BMS CASE STUDY REVIEW



Selected Case: Impact of Hybrid Models

Hybrid Models: Stronger CQA understanding with less data and experiments

The Project:

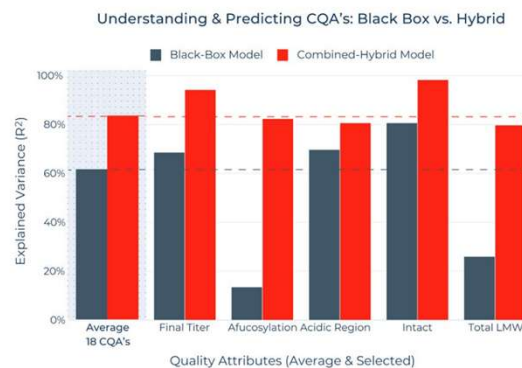
Evaluate the ability of **DataHowLab's Hybrid Models** to accurately predict CQAs compared to industry state-of-the-art "black box" models.

The Challenge:

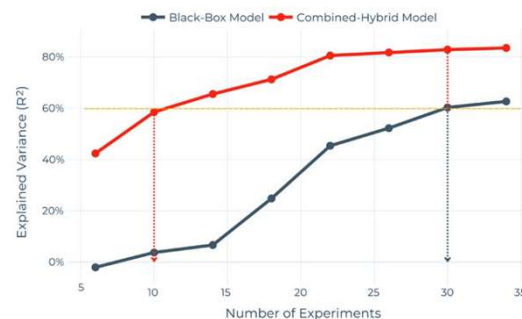
48 (5-liter scale) experiments were designed and conducted by BMS to evaluate the impact of **12 process parameters** on **18 product CQAs**.



Understanding & Predicting CQAs: Black Box vs Hybrid



of Experiments required to predict CQAs: Black Box vs Hybrid



Stronger CQA Prediction & Control

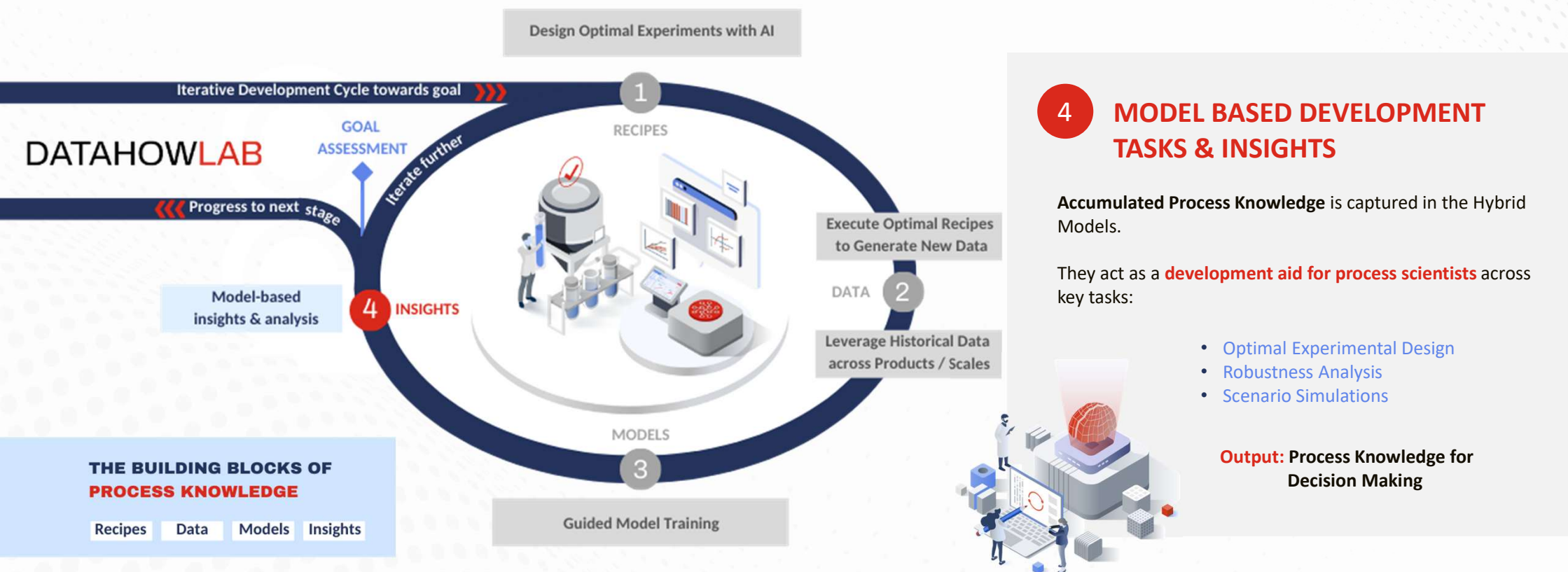
- On average, **Hybrid models** were able to predict CQAs **+35%** better than standard "black box" models
- Hybrid models** were able to predict CQA's where "black box" models had no clear understanding even after 48 experiments

More insight, with fewer experiments

- Black box models needed **30 experiments** before they could accurately predict CQA values
- Hybrid models only required **10 experiments** to reach the same level of predictive accuracy

Use Advanced Hybrid Models for Key Development Tasks

Democratizing Insight Creation & Use across the Process Lifecycle



Selected Case: Optimization of Polishing

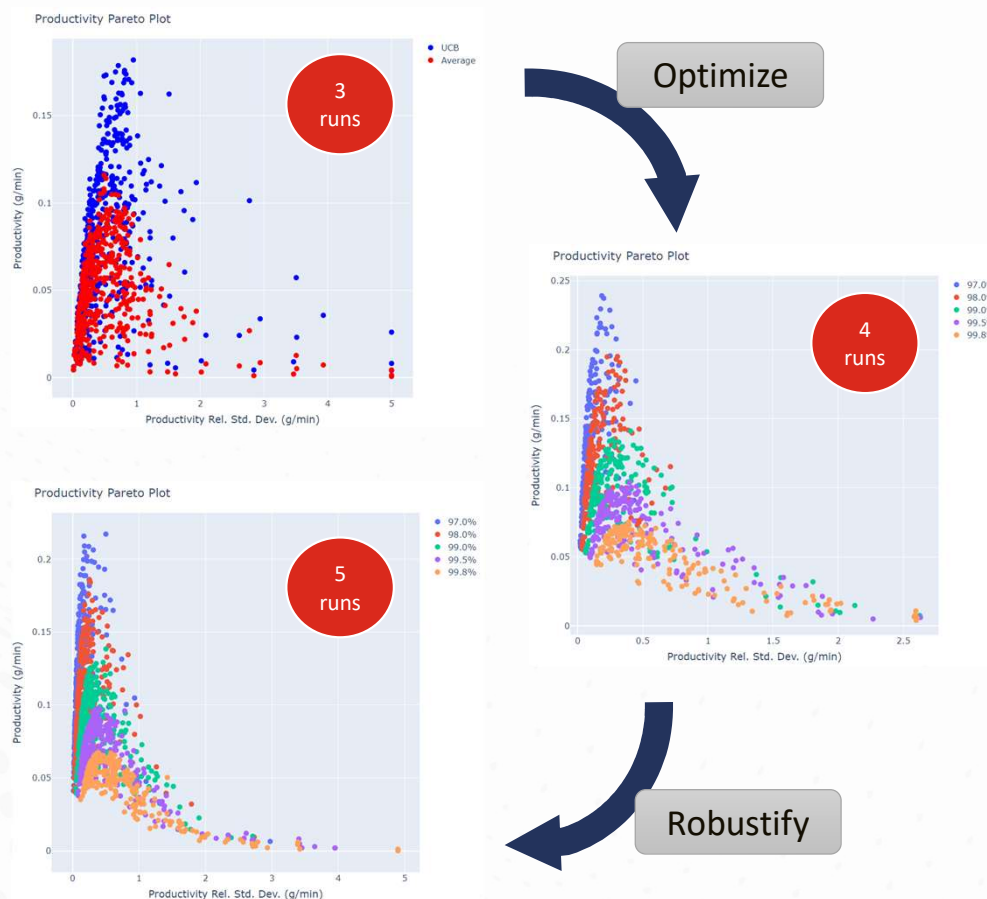
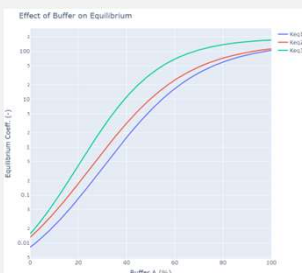
Bayesian Optimization: an optimal trade-off between knowledge and target gains

The Project:

Evaluate the ability of **DataHowLab's Hybrid Models** to accurately optimize a chromatographic polishing step and achieve optimal process robustness with minimum number of experiments.

The Challenge:

In this insilico example, we emulate the separation of **3 components** with a **gradient chromatography** with a complex definition of selectivity vs buffer composition.



Fast learning of process and uncertainties

- With only 4 runs, the **hybrid model** was able to learn the complex adsorption behaviour with competition in the presence of buffer gradient
- The **Pareto curves** supports the users to focus new experiments in promising regions to balance optimization and knowledge gain

More insight, better robustness

- With the Pareto plot, we can easily explore the **trade-off** between productivity and specifications (e.g., product purity)
- Through the Monte-Carlo analysis, we can improve **process robustness**, e.g., sensitivity versus peak cutting

A Structured Development Framework across each Stage

Helping Explore and Exploit the Design Space



DataHowLab

AI-Enabled Digital Bioprocessing Platform



A BIOPROCESS SOLUTION FOR BIOPROCESSING

No-code tools, applications, and workflows are adapted for each process format, operation, and lifecycle, to serve the needs of bioprocess scientists.



DATA AS A DEVELOPMENT ASSET

Transfer insights across molecules and scales to leverage historical data, minimize experimental effort, and accelerate development timelines.



DIGITAL DEVELOPMENT FRAMEWORK

Users are guided through development gates to maximally exploit the use of embedded AI technologies towards process goals.



DIGITAL TWINS & PROCESS SIMULATION

DataHowLab transforms into a digital twin when its powerful hybrid models are combined with process data. True digital bioprocessing.



SINGLE SOURCE OF PROCESS KNOWLEDGE

DataHowLab champions the democratization of process knowledge across the organisation and process lifecycle by storing and deploying insights from shared datasets, projects, and models.



A DIGITAL AUDIT TRAIL FOR YOUR PROCESS

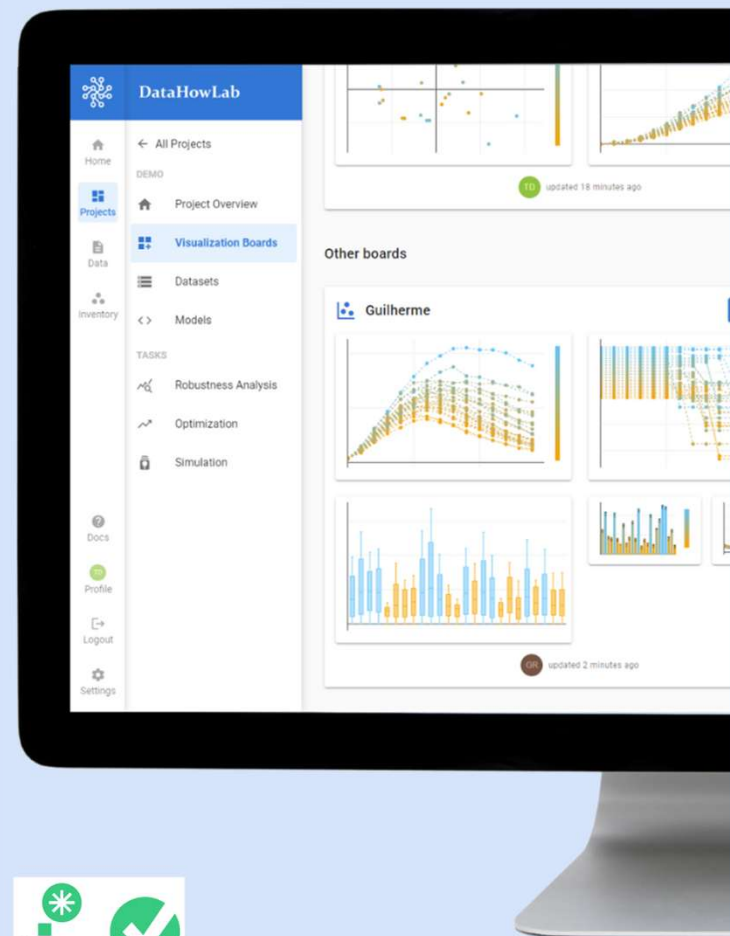
DataHowLab logs every activity taken within the software, providing a detailed audit trail for tech transfer and filing and end-to-end traceability.



POWERED BY AI TECHNOLOGIES ADAPTED TO BIOPROCESSING



DATAHOW



ISO/IEC 27001
INFORMATION SECURITY
MANAGEMENT SYSTEM

Deploying AI-technologies & solutions

Product roadmap and collaboration opportunities

Available in DHL
(Fall 2025)

Available in DHL
(End 2026)

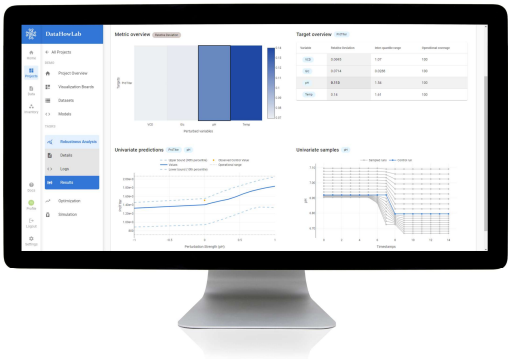
Process format	Cell Culture	Cell Therapy	Microbial	Gene Therapy	mRNA
Unit operation	Upstream	Chromatography	TFF	Formulation	Spectra
Application goal	Screening	Optimization	Scale-up	Characterization	Manufacturing

Available with DataHowLab

Available as innovation project

Commercial use of **DataHowLab**.

Customers able to license DataHowLab, as well as access DataHow’s support services for optimal software usage.

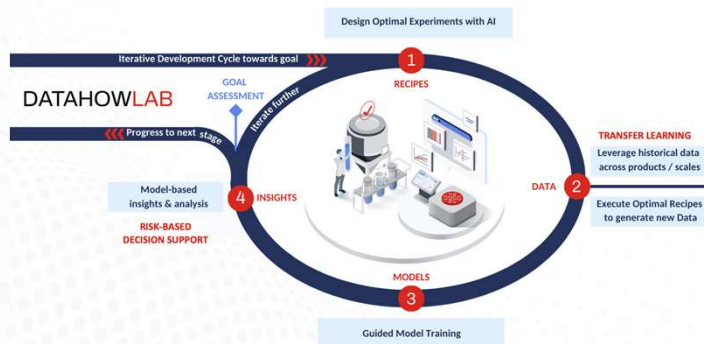


Access to the DataHow team and technology.

Until available within DataHowLab – per the development roadmap – customers are still able to implement the DataHow technology via custom innovation projects across all major and emerging modalities and process operation

Enabling the digital development cycle

Guided for a collaborative and interactive user flow for non-data scientists



DATAHOWLAB

Home

Projects

Data

Results

Project Overview

Visualizations

Datasets

Models

Designs

Tasks

Robustness analysis

Optimization

Simulation

Projects / LOREM-42 Testing

LOREM-42 Testing

Description lorem ipsum

EDIT

Mammalian

Cultivation

3 Products

21 Experiments

12 days

4 hours

27 Variables

1 day ago

Loop #5

CQA Version 7

Design #1

12 Experiments

Dataset #5

Model #12

7 Insights

NEXT LOOP

1 Experimental Planning

2 Experimental Execution

3 Data Preparation

4 Modeling

5 Insights

2/6

Model Purpose

Train/Test split

Accuracy Limitations

Model Type

Overfitting

Variable Importance

Accuracy Limitations

Bioprocesses contain a lot of intrinsic variations. A partially data-driven model is not able to be more accurate than the intrinsic process variability. Understanding this limitation can help understand when modelling efforts are reaching a limit and should not be pushed further.

Suggestions

Identify all true replicates in the dataset.

Learn the replicate error for all my relevant variables.

Datasets

SEE ALL (12)

ADD NEW

Dataset name	Description	Coverage	Updated at	Status
Dataset #1	Lorem ipsum	98%	14.01.2023	SUCCESS
Dataset #2	Lorem ipsum	98%	14.01.2023	SUCCESS
Dataset #3	Lorem ipsum	98%	14.01.2023	SUCCESS
Dataset #4	Lorem ipsum	98%	14.01.2023	SUCCESS

Models

SEE ALL (7)

ADD NEW

Model name	Description	Model type	Updated at	Status
Model #1	Model #1 training	CHM	14.01.2023	SUCCESS
Model #2	Model #1 training	CHM	14.01.2023	SUCCESS
Model #3	Model #1 training	CHM	14.01.2023	SUCCESS
Model #4	Model #1 training	CHM	14.01.2023	SUCCESS

Design Optimizations

SEE ALL (9)

ADD NEW

Robustness analysis

SEE ALL (5)

ADD NEW

Trusted and Deployed by many Key Industry Players



Technology Partners

eppendorf



Academic Partners

ETH zürich



Imperial College
London



Thank you!

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